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The Impact of Personalisation Algorithms on Consumer Engagement and Purchase Behaviour in AI-Enhanced Virtual Shopping Assistants

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The Impact of Personalisation Algorithms on Consumer Engagement and Purchase Behaviour in AI-Enhanced Virtual Shopping Assistants

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Abstract

Algorithms are increasingly used in consumer-oriented decision-making, and understanding how customers respond to them is crucial. The research is grounded in self-determination theory and aims to identify AI algorithm variables that affect consumers' decision-making. These can improve consumers' pleasure, and engagement and boost revenue by increasing customer loyalty. Online shopping involves making purchases through the internet, following a five-phase process. Artificial intelligence is revolutionizing customer engagement by providing tailored experiences and insights. Generative and conversational AI can generate product recommendations, while AI-driven systems offer advantages for both businesses and consumers, boosting sales, and customer satisfaction, and optimizing the shopping process. The study uses Social Exchange Theory (SET) and Service-Dominant Logic (SDL) to study how AI-powered technology can benefit consumers by offering personalized recommendations and quick service.

According to the study, different roles played by algorithmic agents have different impacts on consumers' purchasing decisions. This is consistent with the inverted U-shaped hypothesis. Purchase decisions made by customers have the most influence when algorithmic decision-making autonomy is at a medium degree. The psychological processes and behavioral attitudes of customers towards AI services and buying decisions must be understood. It recommends businesses prioritize personalized algorithm design and raise users' self-efficacy to maintain control over the purchasing process. Understanding customer engagement and balancing AI and human interaction can improve customer engagement strategies and satisfaction.

Key Words: Artificial Intelligence, Virtual Shopping Assistant, Digital Transformation, Business, Chabot etc.

Introduction

Algorithmic decision-making offers several advantages over human decision-making, including being quick, widespread, and low-energy. Because of these characteristics, algorithms are now the basis for decision-making in "algorithmic life," beginning to influence and even take over a growing number of societal issues involving individuals daily (Kochen, 1974). Algorithmic decision-making is already widely employed by the majority of Internet technology corporations in a variety of scenarios and disciplines, including consumer, education, finance, healthcare, transportation, justice, and urban government. Algorithms serve as key catalysts for user engagement, insight, and creativity for businesses that employ them for decision-making. They are not just useful for marketing or sales. It is crucial to comprehend how customers respond to algorithmic conclusions since algorithms are increasingly used in consumer-oriented decision-making (Davis, 2016).

While similar studies have looked at how diverse representations of artificial intelligence products affect customer assessment, there hasn't been much research on how these representations affect consumer purchase choices from the standpoint of algorithmic decision autonomy. This study, which is grounded in self-determination theory, examines how various AI algorithms' decision autonomy affects consumers' purchasing decisions (Luck & Aylett, 2000). The study's conclusions might serve as a manual for algorithm designers, merchants, marketers, and other stakeholders to develop algorithmic marketing strategies, enhance the user experience with AI algorithm decisions, and work more productively and cooperatively with customers to generate value (Lau & Lee, 2018).

Businesses are now relying more on artificial intelligence (AI) to improve the engagement and experience of their customers. Artificial intelligence (AI) has the power to completely change how companies engage with their clients. It is opening up new possibilities to improve outcomes, modernize procedures, and adapt practices. It will delve into the many ways AI technology may be applied to enhance customer interactions, such as chatbots, tailored recommendations, and predictive analytics (Swatman & Chin, 2004).

Research Methodology

Objective of the Study

- To identify the AI logarithms variables that affect online consumers' decision-making on their purchase behavior for items, such as perceived utility, perceived ease of use, and perceived risk.
- To ascertain customer preferences and decisions about websites selling products.

Significance of the Study

AI technologies have the potential to improve consumer pleasure and engagement across a range of activities, which will boost revenue and customer loyalty. AI enables companies to provide individualized marketing messages by analyzing customer data to find trends and preferences. Proactive customer care through chatbots and virtual assistants may boost client happiness and reliability (Vezir OĞUZ, 2018). Additionally, AI may offer recommendation engines and personalized ideas, which raises the possibility of engagement and repeat business. AI may also help companies find ways to improve their goods and services, which will increase consumer contentment and reliability. Predictive maintenance, also known as condition-based maintenance, can assist companies in anticipating maintenance requirements and minimizing equipment failures, thereby reducing downtime and raising customer satisfaction (Ozaki & Takada, 2001). Users are restricted in their access to a variety of information and are bound to the "echo chamber" created by AI algorithms when making decisions based exclusively on algorithmic suggestions based on their interests (Ricci et al., 2023). Our goal is to respond to the following research questions:

Research Questions

1. How do AI algorithmic agents connect socially with customers?

2. Is there a point at which the autonomy of algorithmic decision-making has the greatest impact on customer decisions?

3. What cognitive processes and circumstances underlie the influence of the mediating role of self-efficacy?

The self-determination theory is used in the study to shed light on the causal relationship between algorithmic decision autonomy and client purchasing decisions. Based on how algorithms, humans, and society are related, it divides algorithmic decision autonomy into three categories (Chin et al., 2005). Three researches examine how customer purchasing decisions, consumer self-efficacy, and consumer power distance are affected by algorithmic decision autonomy.

Research Design

The present study was Descriptive research. The survey method was used for the present research paper.

Data Collection

Both primary (interviews, discussions, observations, etc.) and secondary (newspapers, reports, statistical data, journals, books, etc.) data sources are taken into account while going through this research paper. This study employs a qualitative research approach to explore the effects of digital transformation and artificial intelligence on the consumer experience. The data-gathering methodology involves integrating literature review results to identify key themes and patterns in the study report. The researcher will gather relevant literature from academic research papers, business reports, and white papers on AI and the consumer experience in digital transformation. The literature will be assessed to identify key themes, patterns, and research needs. The study will then integrate the results of the literature review and conclude, identifying gaps, contradictions, and common themes across studies.(Hoffmann & Mai, 2022).

To investigate how artificial intelligence (AI) might improve customer experience and engagement, in-depth interviews with customers and business leaders with experience in AI and digital transformation will be undertaken. The research will look at the potential and problems that come with using AI, as well as how it impacts user involvement and experience. The data will be gathered through semi-structured interviews. We will take into account ethical considerations, including getting informed consent, keeping information private, and defending participant rights and privacy. To give organizations chances to enhance their use of AI, the research intends to offer insightful information about how AI affects customer experience and involvement in digital transformation (Romano et al., 2022).

A Review of Literature:

Online shopping is the act of making purchases using the internet. The behavior's five distinct phases are the same as those that make up conventional purchasing behavior. The feeling of a buyer wanting to buy anything is the potential of the online shopping process; therefore, they search for data and other need-related information. The choices that are produced by the information search are assessed, and the best option is then determined to be selected. Finally, the sale is completed, and after-sale services become available (Liang and Lai, 2002). Payment for the items is also made across the net based on the purchase behavior of the clients when they shop online (Ha and Stoel, 2004).

Through their findings, Van Staden and Maree (2005) discovered that their range of items encounters several issues related to online shopping. Certain things are hesitant to be purchased online since traditional buyers are inclined to believe that they need to touch and feel the product before making a firm decision. One of the areas that presented the most difficulties was purchasing apparel since many customers had difficulties making online purchases. The area that just started production showed mixed results, with some consumers preferring to trust the shop staff to do the work, while others were more inclined to select their produce and buy it independently.

According to Haenlein & Kaplan (2019), artificial intelligence (AI), sometimes referred to as human intelligence processes by computers, can transform data into strategies that have a major impact on consumer behavior. According to Ransbotham et al. (2017), AI-based digital marketing further streamlines businesses' ability to reach the appropriate clients at the appropriate moment. With the help of AI, marketers can handle enormous volumes of data, carry out individualized sales, and satisfy customer expectations, claims Jain (2020). According to Davenport (2020), the adoption of intelligent technology solutions for digital marketing is pushing organizations to utilize new technologies like artificial intelligence (AI) and big data to enhance the consumer experience. Khatri (2021) pointed out that AI is used to create marketing plans that work.

Sherman et al. (1997) stated that traditional shopping experiences are influenced by the atmosphere and sensory factors, while online shopping offers a narrower range of experiences and requires specific technological abilities. Due to a lack of expertise, consumers may steer clear of Internet shopping because of things like exchange rules, refunds, return policies, billing issues, and defective items. Though some customers may avoid it because they have trouble browsing websites and don't believe the internet to be a secure place to conduct business, online shopping can still be an engaging experience. Online retailers have an advantage since their marketers frequently offer more thorough product information. E-consumers are more willing to take risks compared to offline shoppers, and online retailers face risks such as uncertainty surrounding transactions, data authenticity and reliability, and insufficient legal material for online retailing. Overall, online shopping offers numerous benefits but also presents challenges for consumers (Whysall, 2000).

According to Andrews and Currim (2004), there might be notable differences in factors such as price sensitivity, the significance assigned to brands, or the choice sets that are taken into consideration in online and offline contexts. Customers weigh the costs and benefits of this environment, weighing their expectations for ease and financial gain from online shopping against uncertainty about products and shopping processes, the retailer's dependability, and other factors (Teo et al., 2004). It is still highly desired that more research be done to fully understand the range of variables impacting consumers' pre-purchase intentions.

Impact of Personalisation Algorithms on Consumer

In a contemporary society characterized by rapidity and competitiveness, enterprises encounter the formidable task of capturing attention and cultivating loyalty as a result of declining spans of attention. But in this specific environment, customization has become an essential element for success. Customizing experiences according to each person's choices, needs, and interests has proven to be crucial for attracting and keeping customers online. When it comes to customization, artificial intelligence (AI) is revolutionizing how businesses engage with their customers (Kulkarni, 2019). Nowadays' customer does not want to be perceived as just another nameless person in the crowd. Instead, they want companies to see them as unique individuals who feel understood and valued by those brands. Personalized marketing and sales methods are becoming the driving forces behind successful marketing campaigns and customer expectations.

Through the use of AI algorithms, businesses can efficiently leverage large amounts of data to get priceless insights and provide their customers with experiences that are highly customized and relevant. In this blog post, we will discuss the importance of customization in customer service and the ways that artificial intelligence is revolutionizing this field. So grab a cup of coffee and come along for the ride as we explore the enormous possibilities that customization offers in the digital age (Pini et al., 2023). By using artificial intelligence, businesses can enhance customer engagement by providing relevant and specialized content that keeps them interested and leads to increased website activity. Personalized guidance and marketing may also boost sales by facilitating customers' search for and acquisition of goods that satisfy their demands (Sang, 2009). Various strategies, including collaborative filtering, content-based filtering, and hybrid techniques, can be used to adapt marketing and recommendations. Combining these strategies can yield better results (Ameen et al., 2022).

The Rise of AI-Powered Personal Shopping Services

As generative artificial intelligence (AI) persists in shaping the ever-evolving realm of electronic commerce, a noteworthy progression within this domain is the emergence of AI-fuelled personalized shopping services. Conveying their purpose through their name, personalized shopping services strive to furnish customers with a bespoke online shopping experience. E-commerce enterprises employ AI-powered personalized shopping services to supplant the necessity of human guidance throughout the entire shopping journey. Instead, these services capitalize on generative AI to assist. Traditionally, high-end department stores exclusively extended personalized shopping services to their esteemed clientele at physical retail outlets (Miles, 2009). Personal shoppers would meticulously select items based on the preferences, requirements, and financial means of their clients. Nonetheless, the idea has completely changed as a result of the democratization and widespread accessibility to these services brought about by the development of digital commerce and AI-powered technology (Jan et al., 2023).

A customer's preferences, style, and financial constraints are understood by AI-powered personalized shopping services through the use of complex algorithms and machine learning. They have instant access to thousands of goods, allowing them to quickly assemble a selection that perfectly suits each customer's needs. Because of this, buying online is easier and more enjoyable, in addition to saving time. A new level of e-commerce Personalisation and internal operational efficiency are being introduced by generative AI, which is completely changing the way these personalized shopping platforms operate. With ongoing improvement and refining, these AI-powered systems become more accurate as they gather more data. Thus, one gets better at understanding one's style and preferences the more often one uses these services. An increasing number of individualized, efficient, and customer-focused retail experiences may be seen in the rise of AI-powered personalized shopping services. The potential for these technologies to transform the retail industry in ways that are now unimaginable exists as long as they continue to advance (Del Valle & Lara, 2023).

Consumer Engagement & Personalisation

Business owners are suddenly realising the value of customization in grabbing customers' attention and meeting their demands, ushering in an era when one-size-fits-all messaging is obsolete. Customer engagement refers to the practice of building and maintaining a relationship with customers that transcends simple transactional exchanges. It means developing meaningful connections, building trust, and adding value for clients at every stage of interaction. When consumer interaction is done right, it may lead to increased customer happiness, brand loyalty, and eventually corporate growth. There are several benefits associated with successful consumer involvement (Rahman et al., 2023). According to research, satisfied customers are more likely to become brand champions, make repeat purchases, and refer others to the business. Additionally, engaged customers typically spend more, which boosts sales and profitability for companies. Engaged customers provide insightful input that helps businesses enhance their offerings in terms of goods, services, and general customer care.

AI Is Powering Personalized Shopping

AI is transforming the operational functions of personal shopping services and introducing a novel dimension of customization to the retail industry. The objective is not solely to enhance the convenience or efficiency of shopping, but rather to curate a personalized experience that resonates with each unique customer. Various forms of AI are employed in personal shopping services, each offering distinct characteristics and advantages. Generative AI can generate novel product recommendations by comprehending a customer's style and preferences at a profound level. Conversational AI engages with customers in real-time, responding to inquiries and suggesting products conversationally. These AI-driven systems present numerous advantages for both businesses and consumers ("FACTORS LEADING TO CONTINUOUS USAGE OF AI SERVICES ON MOBILE SHOPPING," 2020).

From a business standpoint, large volumes of data may be processed quickly and efficiently by AI, which offers insightful information about consumer patterns and behavior. As a consequence, companies may more accurately customize their products and services, which boosts sales and raises consumer happiness. AI also reduces the need for human input, which saves time and money. Consumers stand to gain equally from these benefits. Artificial intelligence-driven personal shopping services provide a highly customized shopping experience by making product recommendations that closely match individual needs and interests. These services ensure client pleasure by lowering the possibility of unpleasant purchases and optimizing shopping by expediting the process (Klaus & Zaichkowsky, 2022).

Generative AI and Personal Shopping Services

A few years ago, the idea of online personal shopping services seemed unthinkable. However, generative artificial intelligence (AI) has completely changed the industry.

Like having a virtual creative prodigy at your disposal, it generates customized suggestions that precisely suit your tastes and aesthetics. Generative AI has had a profoundly transformational effect on the retail industry since it has altered the way that consumers research and make purchases. Generative AI takes a holistic approach instead of depending just on past purchases or browsing behavior. Through its assimilation of data from your behavior, interests, and even outside trends, it combines these insights to provide an extremely precise personalized shopping experience (Sag, 2023).

One of the most remarkable aspects of generative AI is its perpetual evolution and enhancement. It gets more adept at comprehending the wants and demands of its clients as it gets to know their tastes and fashion sense. As a result, over time, generative AI-powered personal shopping services will be able to provide suggestions that are increasingly precise and tailored to your individual preferences. The possibilities for generative AI-powered personal shopping services in the future are virtually limitless. The future of personal shopping is exciting and full of opportunities, from AI-driven chatbots that provide real-time advice to virtual stylists that design ensembles based on your tastes (Moore et al., 2022).

E-commerce companies deploy AI-powered personalized shopping services to eliminate the need for customer support across the whole purchasing process. To help, these services instead make use of generative AI. High-end department stores have traditionally provided their prestigious customers with specialized shopping services only at physical retail locations. Using their clients' tastes, needs, and financial capabilities as a guide, personal shoppers would carefully choose the items for their clients. However, the democratization and widespread accessibility of these services due to the development of AI-powered technology and digital commerce have completely changed the idea. AI-powered personalized shopping platforms employ deep algorithms and machine learning to comprehend a customer's taste, preferences, and purchasing power. They can quickly sort through hundreds of goods to create a selection that meets the specific needs of the buyer. In addition to saving time, this makes internet shopping hassle-free and enjoyable. The operation of these tailored shopping services is being revolutionized by generative AI, adding a new level of internal operational effectiveness and e-commerce customization. These AI-powered systems constantly increase their accuracy through iterative improvement as more data is gathered (Klaus & Zaichkowsky, 2022).

Therefore, when one uses these services more regularly, they get better at understanding their tastes and styles. What effects will this have on buying in the future, then? AI-powered tailored shopping services are on the rise, signaling a move towards more specialized, effective, and customer-focused retail experiences. These technologies have the potential to transform the retail environment in ways that are now unimaginable as they continue to advance (Moore et al., 2022). What does this mean for firms seeking to provide their clients with the most cutting-edge online shopping experiences? Therefore, the obvious question that follows suggests that if they want to establish themselves in the current e-commerce sector, they will need to implement generative AI, conversational AI, and conversational commerce use cases.

The Rising Need for Personalisation

To reach their target demographic, businesses have always relied on extensive marketing efforts and generic messages. However, these strategies are no longer as successful as they once were due to changes in customer expectations. Nowadays, customers demand individualized experiences catered to their requirements, tastes, and habits. This is when customization's power becomes useful. Customizing content, suggestions, and interactions according to unique user information and preferences is referred to as personalization. It helps businesses provide very focused and relevant experiences that connect with customers more deeply. The changing customer landscape is the reason for the demand for customization. According to Accenture, 91% of customers are more inclined to make purchases from companies that they can identify, and recall, and that make suggestions and offers that are pertinent to them (Xashimov & Khaydarova, 2023).

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The Power of Personalisation and Enhanced Customer Experience

Customer-centered marketing strategies prioritize personalization. Businesses may provide customers with a smooth and relevant experience by customizing offerings, recommendations, and content to each person's unique interests and preferences. Customer happiness and loyalty are fostered via personalization, which helps you surpass expectations (Kim & Hong, 2019).

A deep learning model is being developed to provide a comprehensive understanding of consumers, enabling businesses to anticipate future purchases and potential issues. AI technologies are being used to analyze consumer data, allowing businesses to tailor recommendations, promotions, and materials to each customer's needs and preferences. This data is also used to enhance the customer experience, including Amazon's customer customization, loyalty program, warehouse, robotics, and logistical skills (Xashimov & Khaydarova, 2023).

AI and Customer Experience

Television broadcasting, autonomous driving, engineering machinery, healthcare, economics, and internet services are just a few of the sectors and applications that artificial intelligence (AI) has had a major influence on. AI is being used widely, and its intimate relationship with industry and society has improved production and provided advantages (Suriansha, 2023). While fully designed, machine learning (ML), a kind of artificial intelligence, enhances its efficacy by using vast amounts of data. It involves structural algorithms that can forecast, identify patterns in data, and analyze it. A substantial amount of training data—which can be provided as text, photos, audio, or explicitly in databases—is frequently required by machine learning algorithms. The algorithms then sift through this data, looking for characteristics or patterns relevant to the topic at hand. The neural network's "deep" layer count is determined by how many layers it has. Each layer of the network is made up of linked nodes, or neurons, which use the incoming data to perform straightforward computations before sending the results to the next layer. The network gradually can recognize patterns and traits in the input through this approach (Pillarisetty & Mishra, 2022).

Computer vision is an AI technique that uses facial recognition, object detection, and image recognition to understand and recognize visual data from the environment. It is widely used in security systems, driverless cars, and medical diagnosis (Nicolescu & Tudorache, 2022). Traffic signs, pedestrians, and other moving objects are all recognized and tracked by self-driving automobiles through the use of computer vision. The accuracy of computer recognition and interpretation of picture and video data is increased by using methods like deep learning, neural networks, and machine learning to create models from large photo collections. This rapidly growing field offers numerous applications and opportunities for creativity (Yang, 2023).

Chatbots and Virtual Assistance

Chatbots are automated online conversations that operate on the text-to-speech theory, eliminating the need for human labor to respond to multiple inquiries simultaneously. This has become increasingly important as consumer demand for prompt responses to questions, comments, and complaints increases. As businesses aim to grow financially and socially, using chatbots is essential to avoid operational inefficiencies and meet everyone's needs on time (Nicolescu & Tudorache, 2022).

Virtual assistants are also becoming more popular in the workplace, being used to respond to client inquiries, sort orders, and perform other tasks. They are less expensive than full-time employees and can be employed as needed, allowing organizations to scale up or down in response to a fast-changing environment (Yang, 2023). The adoption of virtual assistants in business operations serves as evidence of the need for automation in customer support, reducing reliance on human agents (Pillarisetty & Mishra, 2022). Visual assistants can be basic or complex, depending on the situation, and their algorithm design will differ depending on the task. Implementing a virtual assistant in an organization's customer service department offers numerous advantages, including managing tasks like scheduling, email management, and research. It also helps workers feel less stressed about their jobs, improving work-life balance.

Research on chatbots and virtual assistants has shown that they can enhance customer satisfaction, save costs, and increase efficiency in businesses. Due to the decreased requirement for human personnel to address normal customer service concerns, this can result in cost savings for both businesses and customers. By 2022, chatbots and virtual assistance may save companies up to $8 billion a year, according to research. Moreover, chatbots and virtual assistants can increase productivity and decrease customer wait times by managing multiple conversations simultaneously, fostering customer loyalty. Businesses must ensure proper training and policies for handling challenging inquiries that require human involvement (V et al., 2019).

Lastly, chatbots and virtual assistants have the potential for personalization, as 80% of users of chatbots and virtual assistants are willing to share personal information if it improves their customer experience. This shows that offering specialized guidance and marketing content via chatbots and virtual help may be successful. Overall, the application of AI in customer engagement is promising but requires proper training and collaboration with human agents.

Digital Revolution and Customer Expectations

The digital revolution has transformed the customer experience, making it more adaptable, transparent, and easy. Data privacy is a critical aspect of this technological era, and digital transformation has accelerated communication and transaction speeds while enhancing security and trust. Digital transformation is a crucial process in organizational science and information systems, involving the conversion of an analog system to a digital one. This involves using digital technology to significantly change how businesses operate, manage, and provide value to customers (Dewalska-Opitek, 2023).

This process requires the integration of new digital tools, processes, and business models, as well as modifications to the organizational structure, culture, and strategy. To maintain competitiveness in a rapidly changing business environment, digital transformation adopts a global strategy that prioritizes customer-centricity, innovation, and speed. Customers have been significantly impacted by the digital revolution, which has changed their interactions with businesses and the overall consumer experience. The digital revolution has enabled customers to contact businesses at any time and from anywhere, providing convenience through various digital platforms (Pillarisetty & Mishra, 2022).

Personalization has also become more important, as businesses can collect and analyze customer data to provide tailored experiences. Speed has also increased communication and transaction times between businesses and customers, allowing real-time transactions, assistance requests, and comments. Transparency in business transactions has also increased due to online reviews, social media, and other digital channels. Trust has been built by ensuring transaction legitimacy and protecting customer data through digital technologies like blockchain and encryption.

Theory of Social Exchange

The Social Exchange Theory (SET) suggests that every firm has a give-and-take mentality, with the likelihood of social engagement increasing as benefits exceed drawbacks. SET can be used to study how AI-powered technology could benefit consumers by offering personalized recommendations and quick service, as well as how these aspects affect the customer's relationship with the company. It anticipates client behavior and offers helpful insight, analyzing the effectiveness and persistence of social interactions (Markovsky & Cook, 1989).

According to Service-Dominant Logic (SDL), a company's success is based on its capacity to forge and sustain enduring bonds with its customers in addition to its ability to offer products or services. SDL highlights the significance of interactions between businesses and their consumers. According to this strategy, value is produced by both the firm and the group of customers. In the context of AI, SDL may be used to assess how AI-powered solutions might improve the creation of value and the customer experience.

The Technology Acceptance Concept (TAM) suggests that consumer acceptance and adoption of technology are influenced by claims of efficacy and straightforward usage. TAM suggests that perceived utility and perceived simplicity of use are key factors influencing consumer adoption of AI-powered technologies. Other factors include personal standards, perceived behavioral control, and actual system usage.

Data Analysis/ Overview of the study plan

As a result of data's critical role in value production, distribution, circulation, and consumption in the digital economy, artificial intelligence (AI) algorithms for decision-making have been developed. Due to its speed, ubiquity, and cheap consumption, algorithmic decision-making has become a dominant force in human social affairs. Recommendation engines personalize a large number of online content offerings by using user preferences as opposed to human judgment (Bonnefon et al., 2016). For businesses utilizing these algorithms, it is essential to comprehend how customers respond to algorithmic judgments. Previous research has concentrated on the technological advancements in HCI or the impact of characteristics linked to algorithms on individuals' willingness to accept sophisticated algorithms, according to scientists, enable internet marketers to present customers with precisely the correct good or service, reducing the cost of their search and improving its usefulness. Still, they contend that algorithmic decision-making might weaken users' feelings of agency, which could be detrimental to their well-being and result in algorithmic pollution. Users are restricted in their access to a wide range of information and are connected to the "echo chamber" created by AI algorithms when decisions are made exclusively based on interest-based algorithmic suggestions (Bo and Benbasat, 2007; Danaher et al., 2017).

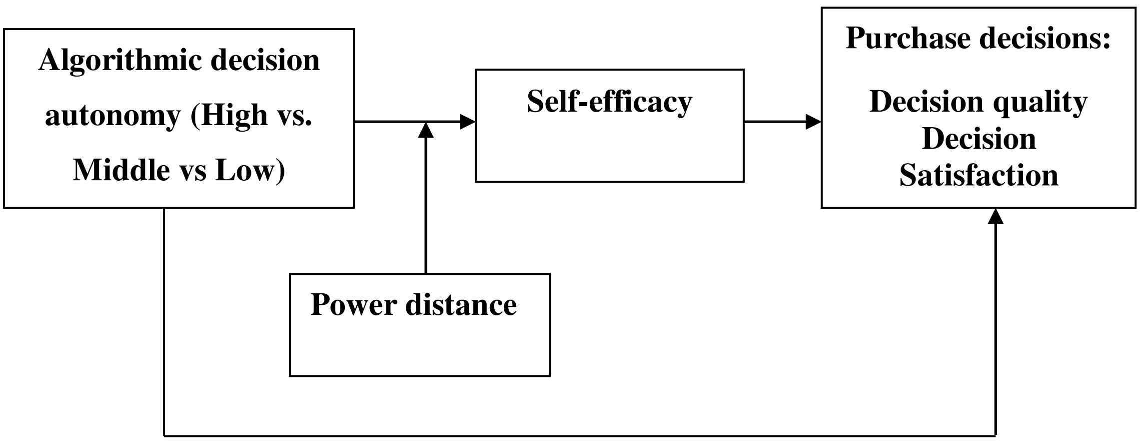

Fig 1 Theoretical Framework

Theoretical background and hypothesis development

Self-determination theory

Three psychological needs—autonomy, competence, and relatedness—that influence consumer behavior are the center of attention for self-determination theory, a motivational theory. Competence is the desire to interact with the world around oneself in an efficient way; relatedness needs are the need to treat people with respect and feel connected to them; and autonomy is the ability to make decisions for oneself free from outside interference.

Customers with high levels of autonomy may feel stifled in their ability to communicate their independent demands, discriminated against, and socially alienated, which may affect their decision to buy. Users exhibit competency by processing algorithmic information more naturally than making algorithmic judgments (Baber, 1996; Rijsdijk et al., 2007; Rijsdijk and Hultink, 2009).

Another crucial component of self-determination theory is relatedness. Excessive degrees of autonomy have the potential to obliterate the distinction between "human" and "tool," endangering human identity and erasing human distinctiveness. This may have a detrimental effect on customers' purchase decisions. On the other hand, self-determination enhances psychological wellness by giving people a sense of control over their decisions and lives. Consequently, SDT provides a clear explanation of how algorithmic decision autonomy influences customer buying decisions.

Algorithmic decision autonomy

The degree of algorithmic decision autonomy refers to how much AI decision systems based on big data, machine learning, and deep learning algorithms work independently and towards their objectives without the need for human involvement. Human decision-making may be challenged by this autonomy, which might result in prejudice, discrimination, censorship, or echo chambers. Furthermore, without the consent of the user, autonomous algorithms may gather data about their behavior and share it with other service providers. This raises concerns about accountability, transparency, justice, and explainability (Baber, 1996; Rijsdijk et al., 2007; Rijsdijk and Hultink, 2009).

The importance of algorithmic decision autonomy is not well understood; however, research by academics and institutional subjects has shed light on the matter. Huang et al. separated intelligence into four categories: mechanical, analytical, intuitive, and empathic. They also combined analytical and intuitive AI into three categories: thinking, feeling, and mechanical. Three categories—narrow AI, general AI, and super AI—are used in some research to categorize AI.

Four categories of AI algorithm jobs were suggested by the OECD (2017): self-learning, signaling, parallel, and monitoring algorithms. Parallel and signaling algorithms, on the other hand, fall under the same category as they are ultimately judgments made by people. Three distinct roles—high, middle, and low—in the social value network correlate to these three varying degrees of autonomy from the standpoint of the human-algorithm choice connection. Studies reveal that one AI product cannot behave autonomously and begins to listen without user intervention at low degrees of autonomy. Up until the point at which more autonomy results in a loss of control, the advantages of increased autonomy may exceed the hazards.

Algorithmic decision autonomy and purchase decisions

Several elements including risk perception, emotions, and cognition, affect consumer buying decisions. Crucial metrics for assessing choice outcomes are decision satisfaction and quality. According to Bechara et al. (1998), decision-making is a cognitive process that requires cognitive processing following the intake of a substantial quantity of data. According to Kuo et al. (2009), emotional shifts brought on by information representation can influence how people behave while making decisions (Bo and Benbasat, 2007).

Algorithms have a high degree of autonomy and diminish human agency when they can make decisions on their own. This increases systemic prejudice against AI algorithms and raises the risk of algorithmic overdependence, which lowers human pleasure. People become less motivated and resistant when they believe AI systems are not meeting their independent requirements. Recommendation algorithm technology, for instance, is used by information distribution systems to sway public opinion and undermine people's reading habits. According to the "uncanny valley" idea, people's reactions to autonomous algorithms may be unsettling and shift from empathy to evasiveness and dread. This can lead to algorithmic decision-loss aversion by obstructing customers' views of how their readiness to embrace algorithms influences the quality and happiness of their decisions.

H1a: Consumers' purchasing decisions will suffer when algorithmic decision autonomy is strong.

When algorithmic decision-making is based on individual user choices, it may increase productivity, deliver the correct services, and preserve customer autonomy. Users feel joy, happiness, loyalty, and a sense of consensus on their recommender system and decision-making when algorithmic decisions meet their demands, according to self-determination theory. They become more satisfied with algorithmic conclusions and have more faith in their judgment as a result. Individualized suggestions facilitate consumers' access to knowledge and superior goods and services, resulting in higher-quality decisions. A greater propensity to accept algorithmic conclusions results from this rise in cognitive and emotional trust. Both social presence and internal motivation for decision-making activities are improved by this. It follows that algorithmic decision-making may improve social presence and decision-making effectiveness (Xiao and Benbasat, 2018).

H1b: When the algorithm's autonomy for making judgments is at the intermediate level, the most comfortable agency connection—has the most impact on customers' purchase decisions.

In the human-algorithm connection, an algorithm turns into a "pure executor" when it lacks autonomy in making decisions. This may have a detrimental effect on decision-making effectiveness, efficiency, and user experience. Moreover, it may result in decision fatigue, which runs counter to current tendencies in digital growth. Furthermore, dated history data and shifting customer preferences may cause algorithms to make decisions based on old, previous data that is then blindly applied. This illogical decision-making might amplify prior errors and compound prejudiced disadvantages (Marjanovic et al., 2021).

Low decision autonomy AI algorithms are defined as mechanical, inflexible, and stiff; they carry out repeated, standardized activities by predetermined protocols. Customers' specific demands are not met by this lack of flexibility, which also makes it challenging for them to engage with AI goods or algorithms. It is hypothesized that to satisfy customer demands, AI algorithms need to be more flexible and adaptive in their design.

H1c: The consumer's choice to buy is negatively impacted when algorithmic decision autonomy is low.

H1: When these three levels are combined, algorithmic decision autonomy affects customers' purchasing decisions in an inverted U-shaped manner.

The mediating role of self-efficacy

Algorithmic decisions are closely associated with self-efficacy or the conviction that one can accomplish their objectives. Empirical studies have demonstrated that users' self-efficacy using personalized algorithms is positively impacted by perceived fairness, explainability, accountability, and openness. The autonomy of artificial intelligence in detecting, thinking, and acting has a beneficial effect on people's perceptions of competence and warmth. Algorithmic thinking and self-efficacy may be enhanced by acquiring algorithmic abilities in a learning environment. Because algorithmic decision-making enhances motivation, cognitive capacity, and action ability, it can assist people in taking control of their external environment (Fanchamps et al., 2021). While algorithms help with motivation and action, decision-making uses up cognitive resources in a task-making setting. H2 is therefore suggested.

H2: Consumer self-efficacy is positively impacted by algorithmic decision autonomy.

An essential component of human performance, self-efficacy affects opportunities, objectives, emotional inclinations, motives, and result expectations. Consumer decision-making is impacted by it; more effective methods are produced by those with stronger self-efficacy. Online self-efficacy improves attitudes toward algorithmic decision-making and boosts confidence in utilizing algorithms. Adoption of healthy habits, recycling, and using fintech are just a few examples of sustainable behaviors that may be accelerated by self-efficacy. Furthermore, it enhances psychological well-being since pleasant emotions and a greater desire to pay for goods are produced by sentiments of self-efficacy connected to one's inventions. As a result, the following theories are put forth:

H3: Consumer buying decisions are positively impacted by self-efficacy.

H4: An Inverted-U link between algorithmic decision autonomy and purchase decisions is mediated by self-efficacy.

Moderating of Power Distance

The term "power distance" describes a person's cultural beliefs and level of acceptance of the unequal allocation of power in society. Individuals who perceive power distance differently tend to have varied preferences when making decisions, which can have an impact on their attitudes and actions. High-power distance people have a stronger feeling of status and self-confidence than low-power distance consumers, who view equality and collaborate with others. When algorithmic decision-making autonomy is great, individuals may lose self-determination and self-efficacy, which lowers their drive to interact with others. Self-determination theory states that people with a large power distance tend to reject using artificial intelligence (AI) to make higher-level judgments because they prefer to make decisions on their own. When making decisions, those who possess a strong sense of power prioritize themselves and act in a more self-centered manner, adhering to the dynamic orientation of power (Rucker et al., 2011).

H5: The impact of algorithmic decision autonomy on purchasing decisions is negatively moderated by power distance.

H6: The impact of algorithmic decision autonomy on self-efficacy is negatively moderated by power distance.

Overview of Studies

To determine how algorithm decision autonomy affected customer purchase decisions, two study scenarios were carried out. While the second looked at the moderating role of self-efficacy, the first used news information distribution networks to analyze the inverted U effect.

Study 1: Main Effect

Pre-study 1

Stimuli and design

Seventy volunteers were gathered for the pre-experiment using the "credamo" online platform, and they were split into three groups at random according to algorithmic decision autonomy. Subsequently, the individuals underwent manipulation tests, judgement questions, and attention questions to assess their decision autonomy. Familiarity and demographic data were also evaluated. The purpose of the study was to evaluate algorithmic decision autonomy at high, medium, and low degrees of autonomy in textual material situations.

Results

The study discovered a substantial variation in the three groups' participants' autonomy in algorithmic decision-making. Individuals with moderate autonomy said the algorithm acted as a "co-assistant" (87.5%); low autonomy believed it was a "pure executor" (82.6%); and those with high autonomy preferred the role of a "dictatorial substitute" (78.3%). The manipulation test's outcomes demonstrated a noteworthy distinction between the two groups, proving the experiment's effectiveness. Study 1 will make use of the experimental environment and data, and the experimental manipulation test was effective in identifying the best algorithmic decision-making approach. The results of the study indicate that the experimental manipulation test is a useful method for further investigation.

Study 1

Design and procedures

Using seven-point Likert scales, the study sought to gauge the quality and satisfaction of customer purchasing decisions. The sample size was determined using a one-way ANOVA statistical test and G*power. 160 clients were recruited for the study using Credamo, and they were subsequently randomly split into three groups. For every group, the sample distribution was Nlow = 53, Nmiddle = 54, and Nhigh = 53. Women between the ages of 18 and 50 made up the bulk of respondents, with an emphasis on those in undergraduate, high school, and college programs. The majority of respondents earned more than 3,000 RMB each month and were managers, students, or clerks. The purpose of the study was to comprehend customer satisfaction and choice autonomy (Amason, 1996; Ameen et al., 2021).

Results

With equal variance homogeneity, the study finds substantial disparities in the participants' autonomy in making decisions among the three algorithm groups. Using several comparison analyses, Dunnett's t-test revealed significant differences between the two groups. Purchase choices are significantly impacted by algorithmic decision autonomy, with the greatest evaluative influence happening at a moderate degree of autonomy. It is also confirmed that there is an inverted U-shaped link between algorithmic decision autonomy and customer purchasing decisions. Using SPSS 26, the regression estimation of the curve was fitted, and the standardized regression coefficients for the main and quadratic factors were significant. The square of decision autonomy is strongly and adversely correlated with the purchase decision, as demonstrated by the inclusion of the independent variable in hierarchical regression after it was squared. With a positive slope at -1.993 and a negative slope at -1.759, the algorithmic decision autonomy spans a range of values from -1.993 to 1.759. Within the range of algorithmic decision autonomy, 0.414 represents the tipping point.

Variables	Purchase decisions (Study 1)				Purchase decisions (Study 2)			Self efficacy (Study 2)		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Control Variables										
Gender	0.143	0.027	0.024	0.244	0.070	0.075	0.162	-0.02	-0.128	-0.128
Age	0.176	0.137	0.103	0.067	0.141	0.173	0.165	-0.034	-0.007	0.012
Education	-0.141	-0.103	-0.204	-0.283	-0.26	-0.243	-0.053	-0.294	-0.287	-0.284
Occupation	-0.052	-0.042	-0.043	-0.023	-0.028	-0.032	-0.017	-0.018	-0.022	-0.023
Income	0..094	0.056	0.105	0.059	0.035	-0.033	-0.012	0.084	0.067	0.067
Familiarity	0.002	0.008	0.087	0.124	0.089	0.122	-0.028	0.243	0.222	0.227
Independent variables										
ADA		0.177**	1.327		0.397***	1.2***	0.978***		0.23***	0.333
ADA2			-0.142			-0.099**	-0.09***			-0.013
Mediator										
Self efficiacy										0.668***
R2	0.03	0.072	0.125	0.044	0.326	0.367	0.602	0.084	0.223	0.222
R2 Change	0.03	0.044	0.055	0.046	0.281	0.044	0.237	0.086	0.138	0.001
F- Value	0.778	1.689	2.691**	1.278	11.13***	11.701***	27.056***	2.513*	6.602***	5.776***
p<0.05;p<0.01;***p<0.001; "ADA" is algorithmic decision autonomy**										

Table 1. Regression results.

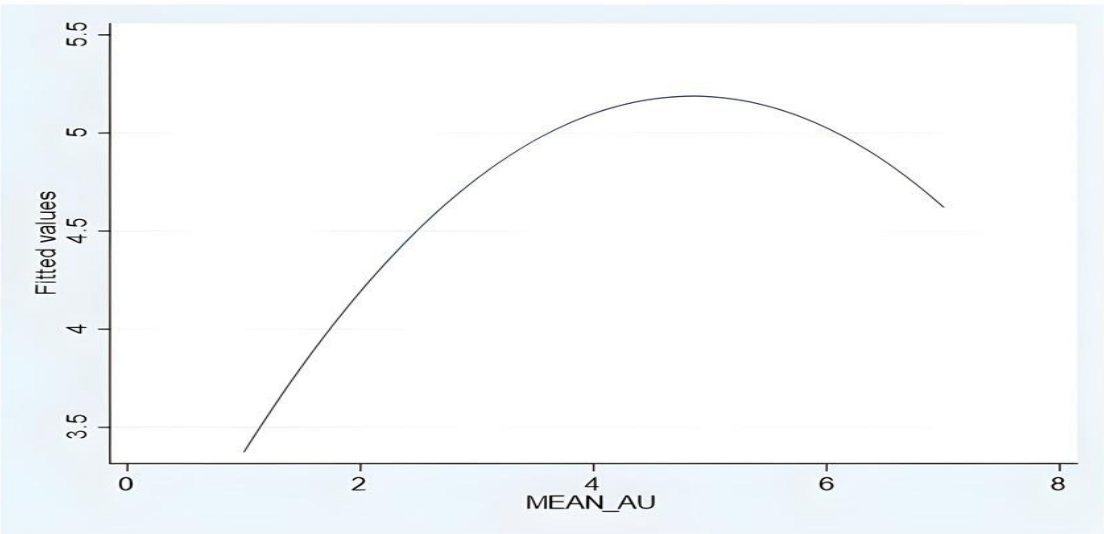

Figure 2. Inverted U-shaped curve fitting (Study 1)

Discussion

According to Study 1, varied roles of algorithmic agents have a considerable impact on consumers' purchase decisions, which is evidence in favor of the inverted U-shaped hypothesis of H1a, H1b, H1c, and H1. With two positive slopes and one lower slope, the relationship between algorithmic choice autonomy and consumer purchase decisions is inverted U-shaped; indicating that the influence of customers' decisions is greatest when algorithmic decision autonomy is in the middle range.

Study 2: Mediating Effect of Self-Efficacy

Pre-study 2

Stimuli and design

Eighty participants were randomly assigned to three groups in pre-study 2 on the choice to buy a home AI service robot. Four questions on algorithmic decision autonomy and one question about the overall manipulation judgement were used to gauge how effective the manipulation was. After the trial, each participant received a prize.

Results

The study discovered notable variations in the three groups' participants' autonomy in algorithmic decision-making. Participants with high autonomy preferred the algorithm over a "dictatorial substitute" role; those with intermediate autonomy preferred a "co-assistant" position. Participants with low levels of autonomy preferred a "pure executor" role. The test of experimental manipulation was effective, and research 2 will make use of the findings.

Study 2

Study design and procedures

Study 2 investigated consumer buying decisions using a one-way between-group experimental design. On a seven-point Likert scale, it incorporated two new elements of choice quality: decision satisfaction and self-efficacy. Using the Credamo platform, 170 individuals were recruited, bringing the sample size to an estimated value of over 159. N-high

= 57, N-middle = 57, and N-low = 56 made up the sample distribution, and 65.3% of the respondents were female. The majority of the respondents (71.2%) were undergraduates, with the age range clustered between 18 and 50 years old. The individuals' occupational distribution was quite equitable, with 69.4% earning more than RMB 3,000 per month. Given that managerial, clerical, administrative, and student responses made up the bulk of the sample, its makeup was appropriate (Köhler et al., 2011).

Results

Using ANOVA analysis, the study looked at how algorithmic decision autonomy affected buying decisions. While a decent degree of autonomy was given to consumers while making purchases, the results demonstrated a considerable influence on outcomes. Significant differences between the two groups were shown by the two-tailed Dunnett's t-test and the mean equality robustness test. The inverted U-shaped effect was validated using regression estimating fit. The findings demonstrated a statistically significant inverse relationship between the square of decision autonomy and purchasing decisions. The algorithmic decision autonomy supported the H1a, H1b, H1c, and H1 hypotheses with a positive slope at -1.992 and a negative slope at -1.704.

Mediating effects

The study looks at how algorithmic decision autonomy influences decisions about what to buy. The absence of an inverted U-shaped association suggests a positive linear impact. Hypothesis H3 is supported by the strong beneficial influence that self-efficacy has on customer purchasing decisions (Lin and Feng, 2022).

Utilizing the study methodology on curve impact in management suggested by Lin and Feng (2022) yields a more precise mediating influence of self-efficacy. Confidence intervals are obtained using the Bootstrap curve mediating test. The findings indicate that the model's overall impact is significant, with a 95% confidence interval for the instantaneous indirect effect's bias-adjusted bootstrap confidence interval. With an effect value of 0.2421, algorithmic decision autonomy has a substantial direct impact on customer purchasing decisions. With an imperfect mediation percentage of 39.140%, algorithmic decision autonomy has a mediating impact value of 0.1557 on purchasing decisions made by self-efficacy. Finally, self-efficacy partially mediates the effect of algorithmic decision autonomy on purchasing decisions, supporting the findings of the H4 hypothesis.

Effects Type	Specific Path	Effect Value	Standard Error	95% Confidence intervals	
				Lower CI	Upper CI
Total effect	/	0.3979	0.0486	0.3020	0.4946
Direct Effect	ADA-PDa	0.2422	0.0424	0.1588	0.3255
Indirect Effect	ADA-SE-PDb	0.1556	0.0416		0.2425
Algorithmic decision autonomy- Purchase Decision **Algorithmic decision autonomy- Self efficacy- Purchase Decisions**					

Table 2. Mediating effects of self-efficacy

Discussions

Research 2 demonstrates that customers' self-efficacy is positively impacted by algorithmic choice autonomy and their purchase decisions. Self-efficacy has a role in mediating the inverted-U link between algorithmic decision autonomy and purchase decisions. The results of hierarchical regression show a strong, albeit declining, adverse link between algorithmic decision autonomy squared and purchase decisions. Consumers' self-efficacy is impacted by the decision-making processes they prefer, which vary depending on power distance. The moderating impact of consumer power distance will be investigated in this study.

General Discussion

Companies are using algorithms more and more to forecast client behavior and make choices that have an immediate impact on both current and new consumers. Because of the necessity to gather and handle customer data while they buy, algorithmic data analysis is moving away from descriptive models and towards predictive ones. However, there are dangers and difficulties associated with autonomous algorithm decision-making, which might lead to human loss of control. Peter F. Drucker cautioned that humanity would struggle to live if they did not learn to regulate the new power that information has extended. In addition to offering insights and managerial suggestions to handle this phenomenon, this research helps our knowledge of how customers react to algorithmic decision-making.

Conclusion

Three studies have examined consumer responses to different levels of algorithmic decision autonomy. Purchase decisions and lesser degrees of algorithmic decision autonomy have an inverse U-shaped connection, according to Research 1. The results of Study 2's analysis of the mediating impact of algorithmic decision autonomy indicate that self-efficacy plays a key role in this connection as it favorably affects customer self-efficacy, which in turn positively influences purchase decisions.

In the era of the digital revolution, AI has the potential to greatly enhance consumer experience and engagement. AI may aid businesses in better understanding the needs and preferences of their customers thanks to its capacity to evaluate vast amounts of data and provide personalized recommendations. Chatbots that are driven by artificial intelligence may provide quick service, and marketing initiatives that encourage conversions and engagement can rise with AI-enabled content. By providing tailored product suggestions, businesses may increase customer satisfaction and loyalty while also improving the overall customer experience. Artificial intelligence can change how customers interact with brands and how they perceive them while giving them the tools to deliver more relevant and customized experiences.

The most crucial thing to keep in mind is that working with businesses to deploy artificial intelligence technology in customer interactions is crucial. Understanding how AI contributes to value co-creation and customer engagement is crucial. By leveraging AI-powered technologies to co-create value with consumers, organizations can boost customer engagement and cultivate loyalty. To reach this degree of success, companies need to pinpoint customer problems that AI-driven solutions may solve and make sure that their AI-powered interactions are accountable, moral, and transparent. In addition, they must manage the ethical concerns brought up by artificial intelligence while defending the right to privacy of their clients.

Understanding the role AI plays in value co-creation and client interaction may help businesses develop strategies that effectively promote customer engagement and loyalty (Chin et al., 2005).

Theoretical study and literature evaluation have demonstrated that AI may enhance customer engagement through tailored and effective interactions and foster value co-creation between organizations and customers. The research's implications for businesses and potential future study topics were also addressed. This study has advanced our knowledge of the potential advantages and restrictions of using artificial intelligence to improve consumer engagement and experience. Businesses may improve consumer experiences and gain a competitive edge in the online market by employing artificial intelligence technologies efficiently.

Theoretical implications

This paper conducts the first empirical investigation into the inverted U-shaped influence of AI algorithmic decision autonomy on customer purchasing decisions, and it offers a thorough explanation and classification of the concept. The results demonstrate that algorithmic decision autonomy performs a more effective middle-level collaborative decision-making function than both high-level autonomous dictatorial replacements and low-level pure executors. By examining the method via which algorithmic decisions affect consumer behaviour, the research also contributes to the understanding of the possible link between algorithmic decision autonomy and customer purchase decisions. Scholars in the field of modern marketing should take immediate action to address these pressing issues, which include designing AI so that consumers will swiftly accept this change in service format and understanding the psychological mechanisms and behavioural attitudes of consumers towards AI services and purchase decisions.

Practical implications

This study emphasizes how algorithmic decision autonomy affects what consumers decide to buy, and it recommends that businesses keep some autonomy in their algorithmic decision-making processes without going overboard. To provide customers with a sense of autonomy and self-control over the purchasing process, businesses should prioritize personalized algorithm design above algorithmic decision-making. It is possible to put up strategies and support protocols that increase consumers' self-efficacy and assist them in overcoming obstacles throughout the decision-making process.

Retail businesses may create the ideal user feedback system and set up an algorithmic application effect evaluation system. Before formally releasing algorithms, they should evaluate how they will affect customers' interests and fundamental rights, take precautions against potential hazards, and set up an algorithm transparency mechanism to reveal information on algorithm adoption. Companies should provide people with the right to seek compensation for algorithmic harm, explain the fundamental ideas underlying the algorithms, enable people to contest algorithmic judgements, and do manual evaluations for decisions that might have a big influence on people and society.

Limitations and Future Research

This study does not differentiate between various sorts of decision tasks; instead, it concentrates on algorithmic autonomy. To understand consumer decision results in various circumstances, it is crucial to take into account the triadic interplay of task type, algorithmic decision autonomy, and person attributes. Studies have demonstrated that algorithms may have a major influence on brand views; however, the study does not investigate how consumers use algorithms to make decisions. In terms of algorithmic choice autonomy, future studies should examine the chain-mediating processes of customers' self-efficacy and purchase decision assessment on brand perceptions. Furthermore, studies by Martin and Waldman indicate that people's views of the validity of utilizing an algorithm decline as decision priority rises. Future studies may thus examine the significance of decisions and enhance the decision-making processes of consumers.

Research on customer engagement and artificial intelligence may eventually aid in identifying the best practices for implementing AI in a variety of sectors and target markets. For example, research can evaluate how customer involvement in sectors like healthcare, banking, and retail is impacted by artificial intelligence. Studies might also look at how artificial intelligence can affect different clientele, such as those from different cultural origins or those with impairments. Research of this nature can assist in identifying any potential biases or restrictions in the application of AI and suggesting ways to overcome them. A Future study can also examine the long-term implications of artificial intelligence on consumer involvement, including how it influences customer loyalty and retention. Such research can provide important information to businesses wanting to improve their customer contact strategies through the use of artificial intelligence (Davis, 2016).

Future research, it is frequently stated, may look into how businesses can balance using AI and human interaction with customers. The use of artificial intelligence in customer service processes has the potential to have a detrimental impact on customer satisfaction if it is overused. To strike a balance, research might examine how artificial intelligence is incorporated into customer service, pinpoint the circumstances that call for human connection the most, and investigate how consumers feel about AI (Lau & Lee, 2018). A balanced approach's impact on client retention, satisfaction, and loyalty might also be evaluated. Finding the correct mix of AI and human connection may help businesses create customer engagement strategies that better utilize the strengths of both technologies.

Declarations

Conflict of interest:

The authors assert that they do not possess any identifiable competing financial interests or personal connections that may have seemed to influence the findings presented in this paper. Furthermore, researchers involved confirm the absence of any potential conflicts of interest related to this paper. The authors affirm that there are no documented instances of competing financial interests or personal relationships that could be perceived as affecting the work described herein.

Human participants and/or animals:

Research did not involve any experiment on the Human Participants and/or Animals.

Informed consent:

Informed consent was collected from all specific participants in the research.

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